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Quantitative Analysis of the Demand for Healthcare Services

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In order to provide the best possible healthcare, managers need effective methods for decision making, as well as effective methods for management and improvement of a healthcare organization. Analysis of the demand is one of the key issues in healthcare organizations in that provides a reliable basis for efficient planning of future activities, of necessary material and financial and human resources. The main aim of this paper is to present the practical implementation of various quantitative methods in order to improve planning and organization of ambulance stations in Serbia. The results of detailed statistical analyses show that demand for emergency medical services follows some hourly, daily and monthly patterns. Observed regularities of the demand should be incorporated in operational, tactical and strategic plans of healthcare organizations in order to improve efficiency and achieve optimal allocation of scarce resources.

Keywords: statistical analysis, multiple regression, healthcare management, demand analysis, modelling emergency medical services,

1. Introduction

Nowadays, when the demand for medical services is growing (Calkins et al., 2016; Eastwood et al., 2015; Veser et al., 2015; Williams, 2015) and the same trend is expected in the future, demand analysis has become an increasingly important area in every organization. On the other hand, due to serious financial difficulties in most of the countries, budgets became even more limited and reduced. Tighter budgets make efficient use of scarce resources extremely important (Jagtenberg et al., 2015). In order to obtain an efficient planning of various activities in healthcare organizations it is necessary to accurately analyse the demand for medical services during the planning period. Goldberg (Goldberg, 2004) mentions that the "ability to predict demand is of paramount importance", but this area has seen little systematic study. A very challenging factor that influences the demand of healthcare services is randomness (Shao et al., 2016), especially when patients arrive without an appointment (which is the case of emergency and radiology departments in hospitals, ambulance service, etc.). The demand patterns tend to be highly time and location dependent and the same can be concluded for the duration of medical interventions. Therefore, classical planning techniques, which assume the deterministic character of the demand, cannot provide a relevant basis for the decision-making process. The adequate demand analysis, which takes into account the stochastic nature of frequency and duration of medical interventions, allows better utilization of available resources that can enable improvements in quality of services, patients' and employees' satisfaction and costs reduction.

The current resource allocations in healthcare organizations in Serbia are static and made ad hoc. This paper provides an insight into dealing with randomness in the ambulance service planning. The literature shows compelling evidence to assume that the level of demand for healthcare services varies over time (Cantwell et al., 2015; Liao et al., 2012; Matteson et al., 2011; Erdogan et al., 2010; Taylor, 2008). Therefore, we can define the main hypotesis that the demand, presented as a number of ambulance calls, depends on the hour of the day, day of the week and month of the year. Taking into account these regularities, it is possible to predict the future variations of the demand and, consequently, human, financial and material resources that should be available at certain periods of time. For this purpose, it is necessary to perform various statistical analyses to examine whether it is possible to determine the daily, weekly or monthly patterns.

Literature review of papers and studies that motivated us the most is presented in the next chapter. Chapter 3 will present the results of the performed quantitative analyses that confirmed the main hypothesis of temporal patterns‘ existence. The last chapter presents the main conclusions and comparison with the results of similar studies, together with the guidelines for future research.

2. Literature Review

Baker and Fitzpatrick (Baker & Fitzpatrick, 1986) were the first who applied Winters exponential smoothing model to obtain accurate forecasts of the daily volume of emergency and non-emergency calls at the ambulance service of South Carolina. To choose the exponential smoothing parameters, goal and quadratic programming were applied. The resulting forecasts were compared to those obtained by using a multiple linear-regression model and a single-objective Winters exponential smoothing model and the smoothing method yielded more accurate forecasts.

Time-series models were developed for the emergency medical service of the Canadian city Calgary (Channouf et al., 2007). The estimated models were compared in terms of goodness of fit and forecasting accuracy. The results showed that an autoregressive model of daily volumes and a multinomial distribution for the vector of number of calls in each hour conditional on the total volume of calls during the day are superior for their data.

Zuidhof (Zuidhof, 2010) analysed the demand of ambulance services in Amsterdam. Holt Winters exponential smoothing models, seasonal autoregressive integrated moving average (ARIMA) models and multiple regression models were used to forecast the daily demand. In this case, the best forecast was obtained by multiple regression model.

In addition to the abovementioned univariate and multivariate time series analysis, artificial neural network can also be designed to forecast the demand for healthcare services of specific areas during different times of the day (Setzler et al., 2009).

A group of authors (Filho et al., 2012) used the Constraint Satisfaction Problem approach to solve human resource allocation problems in cooperative health services. The authors proposed a new tool for planning human resources utilization in hospital plants by using simulations for measuring the performance of the proposed heuristics.

According to the latest literature (et al., 2015), the ambulance demand estimation at fine time and location scales is critical for fleet management and dynamic deployment. In this paper authors introduced a novel characterization of time-varying Gaussian mixture models in order to address spatial and temporal patterns of the demand. The proposed model gives higher statistical predictive accuracy to reduce the error in predicting emergency medical service operational performance by as much as two-thirds compared to a typical industry practice.

A group of authors (Nickel et al., 2016) investigated the problem of choosing the location and number of ambulances and their bases in a certain region. The goal was to minimize the total cost for installing these facilities while assuring a minimum coverage level under stochastic demand. The authors showed that even when demand can be captured by a finite number of scenarios, the number of scenarios rapidly becomes too large, thus preventing the effective use of the model. They also showed that the possibility of considering just one sample of scenarios can lead to a totally misleading solution. These insights motivated them to develop a sampling approach. The sample of optimal values obtained by this procedure can be combined in order to estimate the optimal value of the original problem.

The usual organizational problem of many healthcare organizations is that the number of available staff has been determined ad hoc, regardless of the demand and system load, which might negatively influence the efficiency of the whole system. Here, the application of queueing theory in healthcare organizations might improve patients’ and employees’ satisfaction by reducing the time spent in waiting lines (Bekker & DeBruin, 2010), (Yankovic & Green, 2011), (Brahma, 2012).

Besides the queueing theory and other analytical methods, simulation models are frequently used for modelling various processes in healthcare organizations. A group of authors (Ghanes et al., 2015) used discrete event simulation on order to determine the best way of staffing in the emergency department in one French hospital. DeRienzo (DeRienzo et al., 2016) et al. developed a discrete event simulation model of nursing staff needed in a neonatal intensive care unit and then validated the model against historical data. They assume that the discrete event simulation tool model can provide healthcare managers a valid method of modeling patient mix, patient acuity, staffing needs, and costs in the present state and the future state.

In a recently published paper (Vile et al., 2016) the authors investigated several interrelated advanced statistical and operational research methods, culminating in a suite of decision support tools to aid the Welsh Ambulance Service Trust with capacity planning issues. The developed techniques are integrated in a master workforce capacity planning tool that may be independently operated by planners. By means of incorporating methods that seek to simultaneously better predict future demands, recommend minimum staffing requirements and generate low-cost rosters, the tool ultimately provides planners with an analytical base to effectively deploy resources.

3. Methodology and Statistical Methods

In this paper, the demand for healthcare services is presented by the daily number of ambulance rides at the Ambulance Service in Subotica, Serbia. The data set provides us with the information about the daily number of ambulance rides and occupancy times during a three yeas period, from March 15th, 2011 until March 15th, 2014. With the aim of identifying yearly and weekly regularities in the recurrence of ambulance calls, the applied methods include the correlation analysis statistical method (Spearman's and Kendall's rank correlation test), nonparametric tests based on rank sums (Wilcoxon T test and Mann-Whitney U test), contingency tables and a multiple regression model.

3.1. Preliminary Data Analysis

Based on the box-and-whisker plot (Figure 1), the median can easily be noticed as a value of the numeric characteristic with the highest frequency. The central part of the diagram, the box plot, covers 50 percent of the total observations, which are between the 25th and 75th percentile. In the observed period, an average of 30 medical interventions was made within a single day. The highest number of daily interventions was 54, and the lowest number was 13. The value of the standard deviation amounted to 6.63, while the value of coefficient of variation was 22.14 percent. Thus, it can be concluded that the data show moderate oscillations in relation to the average number of daily ambulance rides.

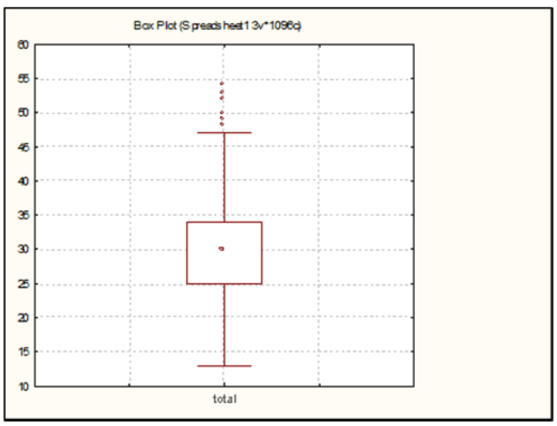

Figure 1: Box-and-Whisker plot of a daily number of ambulance rides

The Jarque-Bera test statistic has been applied as a joint testing of skewness and kurtosis. Since the given value of this statistics exceeds the critical value of 9.21 (at the confidence interval of 99 percent), we can reject the null hypothesis about the existence of the normal distribution and conclude that the data fail to follow a symmetric normal distribution.

By analysing Figure 2 we can see that the most frequent period of a year is spring (March, April and May) and the months that are characterized by the lowest number of interventions are September and June. Figure 3 shows that the demand for emergency medical services increases during the weekend, while the middle of the week is characterised by a lower number of daily interventions. Those conclusions are also confirmed by the multiple regression model, which is presented in chapter 3.3. The number of medical interventions is significantly higher during daytime than at night, and the most frequent hours are from 10-11 a.m. and 7-8 p.m. (see Figure 4).

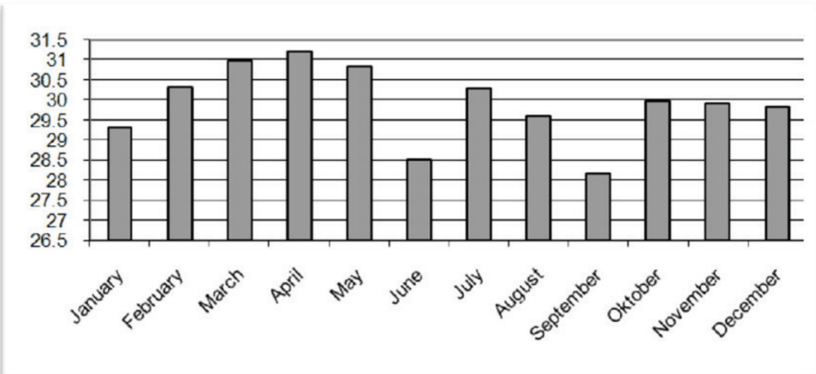

Figure 2: Mean number of ambulance rides per day, for each month of the year

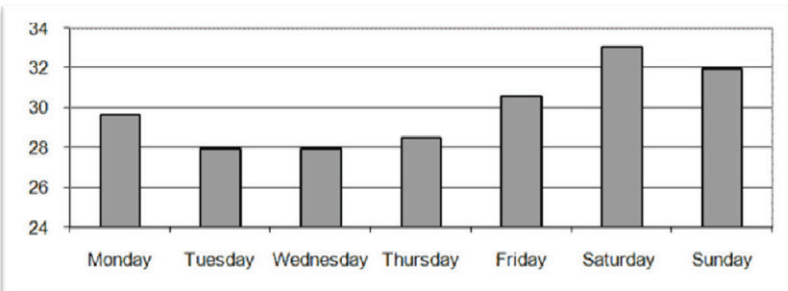

Figure 3: Mean number of ambulance rides per day, for each day of the week

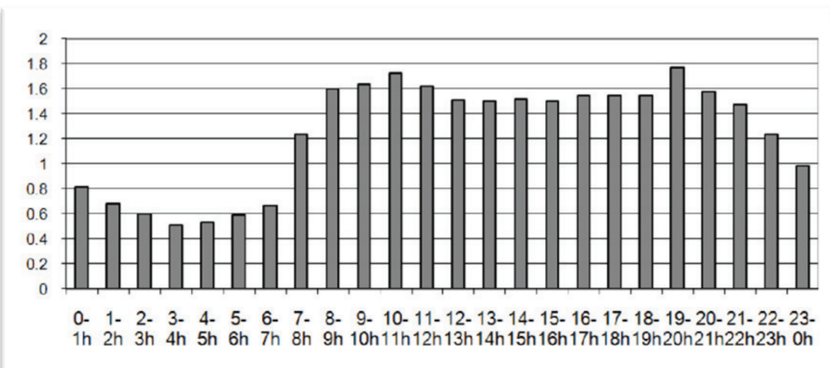

Figure 4: Mean number of ambulance rides per day, for each hour of the day

It is also necessary to analyse the travel time of ambulance rides, which is defined as the time between the starting time of the ride and the time the ambulance is available again. During this time the ambulance cannot respond to new incoming calls. The duration of travel times depends on various and numerous factors. Frequent variations of travel times are also reflected in high values of standard deviation in comparison with the average travel time. The travel time of ambulance crews is characterised by significant oscillations (Figure 5) and the results of the Jarque-Bera test statistics show that the data do not follow the normal distribution. Figures 6 and 7 show how travel time varies over the day and the week.

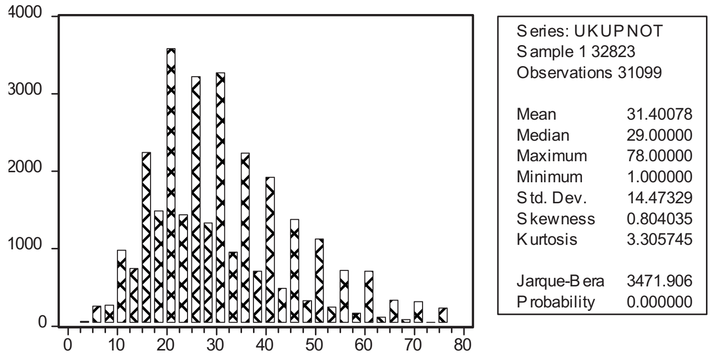

Figure 5: Histogram and basic statistics of travel time of ambulance rides (in minutes)

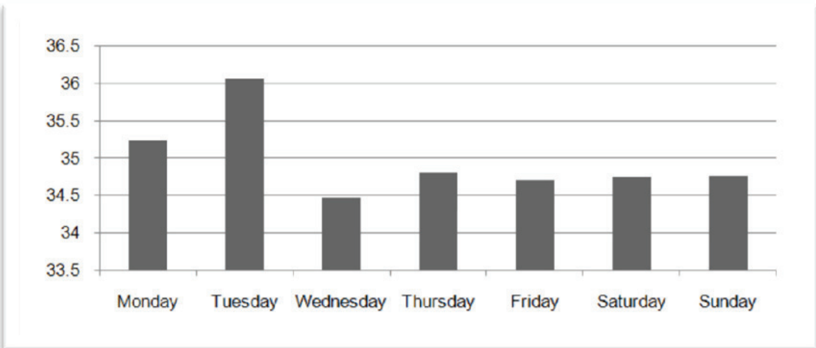

Figure 6: Mean travel time of ambulance rides for each day of the week

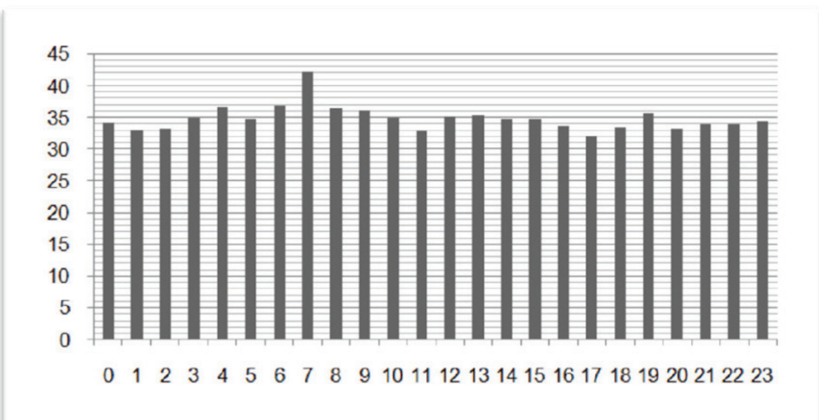

Figure 7: Mean travel time of ambulance rides for each hour of the day

The correlation analysis involves examination of the relationship between the observed phenomena. Extreme observations, indicated in the above paragraph, will be left out from the analysis in this chapter, because they considerably influence the reliability of the correlation test results. After the application of Spearman and Kendall's coefficient correlation test, it can be concluded that the number of daily interventions correlates positively with the number of interventions the day before. The number of daily interventions also correlates positively with the number of interventions made two days earlier and one week earlier. In all cases, the confidence interval was 99 percent. Furthermore, detailed analyses will be made to examine whether the number of ambulance rides depends on a specific day of the week and whether certain days have a similar pattern of recurrence.

3.2. Examination of Weekly and Daily Patterns

The positive correlation of the current number of ambulance rides with the number of ambulance rides made a week earlier indicates that the work load of the ambulance service may depend on the day of the week. It is necessary to examine whether the frequency of the number of ambulance rides during the week significantly differs from the days of the weekend. Based on the results of preliminary data analysis we assume that there will be a significant difference and in this subchapter we will test this hypothesis. For that purpose, nonparametric Mann-Whitney U test, which verifies whether two independent samples belong to the same population, will be applied. This test provides reliable results when the sizes of subsamples are different (Mann & Whitney, 1947).

The computed value of the U statistic is 107995.5, so we accept the alternative hypothesis on the existence of difference between the distributions of data in two sub-samples at the confidence interval of 99 percent. The results show that during the weekend the number of ambulance rides is significantly higher than the number of interventions during the workdays. Thus, we confirmed one of the hypotheses of this paper, that the number of ambulance rides is significantly dependent on the part of the week (weekend or workdays) and further regression analysis (chapter 3.3.) will present a more detailed explanation of those effects.

In addition to the previously identified weekly patterns, it is also necessary to examine whether the daily patterns exist as well. In this part of the paper we will test the hypothesis that the intensity of demand for ambulance services depends on the hour of the day. Figure 8 below displays data about the total number of ambulance rides depending on the hours of the day and days of the week. We can see that the demand for ambulance services is higher during the day than during the night hours, and a majority of interventions are concentrated between 8 a.m. and 8 p.m.

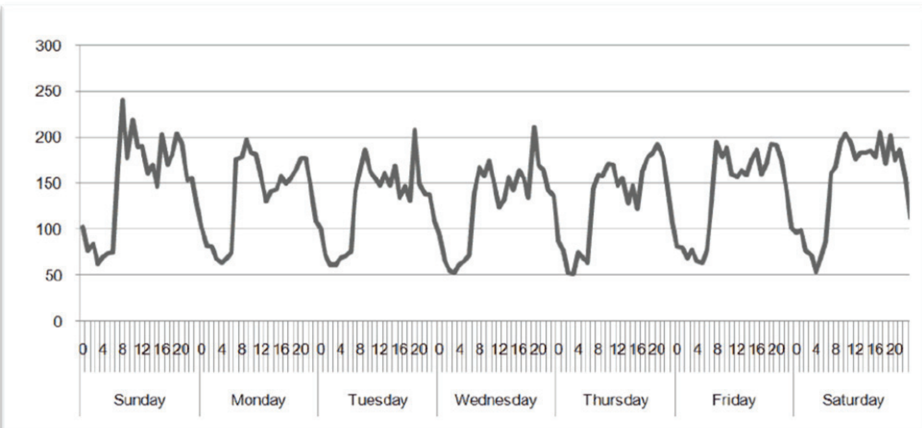

Figure 8: Mean hourly volume of ambulance rides on every day of the week

Furthermore, we will apply contingency tables in order to provide accurate conclusions whether the number of ambulance rides per hour differs on specific days of the week and whether it is possible to group the days which have similar daily patterns of the demand. Thus, it should be checked whether the distribution of the demand differs on individual days of the week. If it does, it is necessary to examine whether there are days on which the difference in the distribution is not significant, so we define the groups of days which follow the same daily pattern.

Figure 8 shows that the distribution of the demand for ambulance services differs over week. This conclusion has also been confirmed by the χ^2 test since the obtained test statistic value is $\chi^2= 189.88$. It can be concluded that the significant difference in the distribution of the demand during various days of the week exists, so we confirmed the hypothesis stated in this subchapter. Further, we should check whether some days have a similar pattern of demand or whether the distribution of the demand is unique for all days of the week. Based on the χ^2 test results, we can conclude that days characterised by similar distribution of the number of ambulance rides can be grouped in three categories. The first group consists of Tuesdays and Wednesdays, where the value of corresponding χ^2 statistic is 27.78. Fridays, Saturdays, Sundays and Mondays belong to the second group for which the value of χ^2 statistic is 84.68. On Thursdays, the distribution of the number of interventions statistically differs significantly from other days of the week, so that day of the week makes the third category.

3.3. Multiple Regression Model

Our previous analysis confirms the presence of the month of year and day of week effects, hence we need to make use of a model which takes all categories into account altogether. This is done using the multiple linear regression model (Zuidhof, 2010; Channouf et al., 2007). An interesting question is also whether certain public and religious holidays significantly influence the level of demand for ambulance services. Therefore, we can use multiple regression to model the behaviour of daily demand for ambulance services. We have multiple explanatory variables, month of the year, day of the week and public and religious holidays, which we model in a linear manner. The holidays that will be included in the model are: New Year holiday(31st December and 1st January), Easter (Julian and Gregorian calendar) and Christmas (Julian and Gregorian calendar). The next equation presents the linear multiple regression model:

$$Y_t = a + \sum_{i=1}^{12} b_i B_{i,t} + \sum_{j=1}^{7} c_j C_{j,t} + \sum_{k=1}^{6} d_k D_{k,t} + u_t \qquad (1)$$

where Y_t is the t-th observation of the number of daily rides, indicator $B_{i,t}$ has value 1 if the month of day t is the i-th month of the year and value 0 otherwise, the indicator $C_{j,t}$ has value 1 if day t is the j-th day of the week and 0 otherwise and the indicator $D_{k,t}$ has value 1 if day t is the k-th holiday and 0 otherwise. Parameters of the regression model *are* b_i, c_j, d_k and u_t is the error term. The application of the regression model demands that residuals are i.i.d. Gaussian distributed. Estimates of the parameters are obtained by using the least square method to minimize the sum of squares of the residuals. To avoid the problem of multicollinearity it is necessary to set the linear constraints on parameters as follows:

$$\sum_{i=1}^{12} b_i = 0, \sum_{j=1}^{7} c_j = 0, \sum_{k=1}^{6} d_k = 0 \qquad (2)$$

Table 1: Significant parameters of multiple regression model

Parameter:	a	b_4	b_6	b_9	
	Constant	April	June	September	
Coefficient:	29.821	1.324	-1.087	-1.541	
Parameter:	c_2	c_3	c_4	c_6	c_7
	Tuesday	Wednesday	Thursday	Saturday	Sunday
Coefficient:	-1.874	-1.902	-1.395	2.945	2.153

Table 1 presents the significant parameters of the estimated multiple regression model. In this model significant factors for the parameters month of the year and day of the week, ($p< 0.05$) are April, June, September, Tuesday, Wednesday, Thursday, Saturday and Sunday. According to the presented results, public and relogious holidays do not have significant influence on the daily number of ambulance calls. The average daily number of ambulance calls is 29.82, while the busiest month is April. During June and September the level of daily demand for ambulance services is lower than average. This model also confirms the existence of temporal pattern during the week. During the weekend an expected number of ambulance calls is higher than average by 2.945 calls on Saturday and 2.153 on Sunday. The middle of the week is characterized by the demand which is below the daily average. The estimated multiple regression model allows us to calculate the expected number of daily ambulance calls by incorporating both month of the year and day of the week effects. For example, the Saturdays in April will have the highest expected level of demand of 34 calls per day (29.821+1.324+2.945= 34.09). The lowest demand of 26,4 calls per day can be expected on Wednesdays in September (29.821-1.541-1.902=26.378). Thus we can now conclude that the results of the estimated multiple regression model confirm the basic hypothesis of this paper, that month of the year and day of the week significantly influence the demand for ambulance services. The presented information is very useful for linking demand (in this case, emergency call volumes) and supply (human, financial and material resources) to aid the decision-making process in healthcare organizations, in order to obtain a desired level of medical services at reasonable costs. The identified temporal patterns provide valuable input data for the development of various quantitative models for forecasting future demand (DeRienzo et al., 2016; Matteson et al., 2011; Channouf et al., 2007), staffing and scheduling employees in healthcare organizations (Ghanes et al., 2015; Yankovic & Green, 2011; Ernst et al., 2004) or obtaining an optimal resources allocation in other fields in order to improve the overall quality of healthcare services provision (Schneeberger et al., 2016).

Conslusion

This paper provides an insight into dealing with randomness in the ambulance service planning. Emergency medical services play a crucial role in the overall quality and performance of health services and the effectiveness of emergency medical services is a crucial ingredient of an efficient healthcare system (Erdogan et al., 2010). The performance of these systems heavily depends on operational success of emergency services in which emergency vehicles, medical personnel and supporting equipment and facilities are the main resources (Coskun & Erol, 2010). Recently, there has been a wide interest in the planning of emergency medical services and many models and approaches have been developed in order to use ambulances efficiently (Chen et al., 2016; Jagtenberg et al., 2016; Su et al., 2015; Wankhade & Mackway-Jones, 2015). The analysis of the demand is one of the key issues in healthcare organizations; it provides reliable basis for an efficient planning of future activities and necessary material, financial and human resources. While the goal of operations research is to aid decision makers, implementation of published models occurs less frequently than one might hope (Green & Kolesar, 2004). Unfortunately, practical application of quantitative methods in the healthcare sector in our local community is on an extremely low level. Some possible reasons for this situation might be low levels of engineering/mathematical background in the healthcare sector, lack of process-related data for modelling, lack of in-house operations research expertise and high cost of engaging external consultants (Teow, 2009). The main aim of this paper is to present and encourage a practical implementation of various quantitative methods in order to improve the planning and organization of ambulance stations in Serbia. This is one of the first papers that combine quantitative methods and healthcare management in this country. The results of detailed quantitative analyses show that demand for emergency medical services follows some hourly, daily and monthly patterns. The observed regularities of the demand should be incorporated in operational, tactical and strategic plans of healthcare organizations in order to improve efficiency and achieve optimal allocation of scarce resources (Ernst et al., 2004). The application of quantitative models greatly accelerates and simplifies the process of decision making, which is especially important in complex healthcare organizations. Integration of quantitative methods, management and health is necessary in order to improve the overall healthcare system in the today's rapidly changing environment. Taking into account the social significance of this topic, extensive world literature and a lack of systematic study in this field in our local environment, there was a need for conducting such a research, with the belief that the results of the research process will contribute to a deeper and more comprehensive review of issues concerning the modelling of demand in healthcare institutions. Special emphasis needs to be placed on the practical significance of this research, because the use of the original data has enabled the future implementation of new or already developed models in order to improve the business organization of ambulance services in Serbia.

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